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Abstract

This paper examines how the effects of increased employment growth on a metropolitan area's employment to population ratio varies with the initial tightness of the metropolitan area's labor market. This examination is relevant to evaluating the benefits of local economic development policies in different metropolitan areas. Much of the benefits of such policies are in higher employment rates. The empirical estimates suggest that the effectiveness of employment growth in increasing the employment to population ratio is lower in metropolitan areas with "tight" labor markets. In addition, some estimates suggest that growth has the greatest long-run effects on the employment to population ratio in metropolitan areas with some looseness in labor market conditions, compared to metropolitan areas with the most tight or most loose labor market conditions. Growth pays off the most for metropolitan areas that have above-average labor market problems, but not too much above average.

This paper examines how the effects of local employment growth on local employment to population ratios vary with the initial "tightness," as opposed to "looseness," of the local labor market.

Local employment growth must either increase local employment population ratios, or local population. One would think that if the local labor market is "looser"—has more effectively available labor supply—then a shock to local employment growth will have more of an effect on local employment/population ratios. In contrast, if little local labor supply is available (the local labor market is "tight"), then a shock to growth would be expected to be reflected more in increased in-migration.

Although this may seem an obvious topic, to my knowledge there has been no research providing evidence on this issue.

Why do we care? We might care about this topic for at least three reasons. First, from a local perspective, the benefits of promoting local job growth, through economic development policies or other policies, are likely to be greater when more new jobs go to local residents, and fewer of the new jobs go to in-migrants. In-migrants may not "count" as much from the perspective of local policymakers. In addition, migrants, who were otherwise on the verge of choosing another similar local economy, will find their well-being little affected by extra job opportunities in this one local area. In contrast, local residents who are not on the verge of moving out have strong and valuable ties to this local area, and therefore may benefit greatly from greater local job growth (Bartik 1991). Therefore, even if local policymakers put similar weight on the interests of the original local residents and in-migrants, jobs that go to local residents may have greater benefits.

Second, differential effects of local job growth on employment rates could, under some models, be one way in which local economic development could be a "positive-sum game." It is common for economists, policy advocates, and policymakers to argue that the economic development wars among state and local governments are a zero sum game from a national perspective. If one area attracts jobs, and these jobs would have otherwise gone to another local area, it would seem that the net benefits to the area that gains jobs are completely offset, from a national perspective, by the jobs lost to the other local area. But if job growth has greater employment rate effects in some types of areas, then this need not be the case. Labor demand shocks that redistribute employment and population toward areas with a more responsive employment to population ratio may raise effective national labor supply and hence raise national employment.

Third, many federal policies, policymakers, and researchers consider it desirable to target some government programs on local areas with greater labor market "distress." But how does one measure labor market distress? Some labor market programs base funding on local unemployment rates. This paper explores which particular measures of initial labor market distress are most correlated with the employment rate effects of job growth. If shocks to job growth only increase in-migration, one could argue that the local residents do not need extra assistance to get better jobs.

Using pooled cross-section time-series data, with the observations being the change from one year to the next in means for metropolitan area/year cells, and with the data including 38 metropolitan areas from 1979–1980 to 2003–2004, this paper estimates that local growth's effect on local employment rates is significantly higher in the short run for metropolitan areas with initially looser labor markets. In the longer run, the variation in effects of local employment growth on local employment rates do not vary as much or as systematically with local labor market conditions. However, there is some evidence that local growth's effects on local employment growth rates are smaller in areas with the initially tightest labor markets, compared to areas with average labor market tightness.

THEORY

It is mathematically true that the employment in a local economy can be expressed as the product of the economy's employment rate and population, or

$$(1) \qquad E_{mt} = (E_{mt} / P_{mt}) * P_{mt} .$$

Taking natural logs, and differentiating, we get

$$(2) \qquad \mathrm{dln}E_{mt} = \mathrm{dln}(E_{mt} / P_{mt}) + \mathrm{dln}(P_{mt}) .$$

Equation (2) implies that in response to any shock we might consider, the "logarithmic percentage" change in local employment must be exactly divided up between the logarithmic percentage change in local employment rates and the logarithmic percentage change in local population.

Therefore, when a metropolitan area pursues economic development policies to increase its local employment growth, any resulting increase in employment growth must lead to some mixture of increases in local employment to population ratios and increases in local population. There is no other possibility. For the same level of growth, economic development policies that increase local employment to population ratios more will increase local population less, and vice versa.

The increase in local employment rates vs. local population due to employment growth shocks might vary with the local labor market's initial tightness. If more local labor is available, employers might find it easier to fill job vacancies through local hiring. In addition, empirical evidence suggests that the effects of local unemployment on local wages are highly nonlinear. Wage curve studies show that a decline from 8 to 6 percent in local unemployment, compared to a decline from 5 to 3 percent, causes a smaller increase in local wages (local wages appear to vary with the natural logarithm of the local unemployment rate; see Blanchflower and Oswald [1994]). If higher local wages have more effects on population in-migration than local labor force participation rates, then the nonlinear effects of unemployment on local wages suggests that a growth shock in an initially high unemployment area, compared to a low unemployment area, will lead to less population in-migration.

Benefit-cost analysis of local economic development policies suggest that, from a local perspective, most of the benefits of faster local growth are local labor market benefits, which are increases in earnings that occur either because local residents are more likely to be employed or get better jobs. Local increases in property values or fiscal benefits are likely to be much smaller. For example, in a recent empirical analysis, Bartik (2005) concluded that the labor market benefits of attracting jobs through economic development are likely to be at least two and a half times the fiscal benefits, and at least four times the benefits in increased property values.

Furthermore, Bartik (2005) finds that over half of the labor market benefits of growth occur due to increased employment rates of local residents. Of the labor market benefits in this 2005 study, over half occur due to increased employment rates of local residents. In general, the more that job growth increases local employment rates, the higher the benefits.

In addition, higher population growth tends to reduce the fiscal benefits of growth. It is believed that businesses tend to pay more in state and local taxes then they receive in services, whereas the average household tends to require more in public services than they pay in taxes (Oakland and Testa 1996). Holding employment growth constant, extra population growth is likely to generate more public service costs than the extra tax revenue generated.

This benefit-cost analysis overlooks the potential benefits of local growth either to induced in-migrants that occur because of the extra local growth, or the diverted out-migrants who decide to stay because of the growth. These effects on migration flows boost local population. One could decide to ignore in-migrants because they are not part of the original local population, so they “don’t count” from a local perspective. However, even if they do count, there is a strong argument that in-migrants’ opportunities and well-being are little affected by what happens in this one local area. In-migrants could otherwise have moved to another local area that was quite similar.

The diverted out-migrants do experience a benefit from stronger local growth, but it is likely to be smaller than benefits to local residents who would have stayed regardless of the growth. Persons who would have moved out without the growth shock are likely to be individuals with less valuable ties to this local area, and with better opportunities elsewhere, compared with those who would have stayed regardless. Weaker local ties and better opportunities elsewhere tend to reduce the benefits to diverted in-migrants from faster growth in this local area.

The bottom line is that the local benefits of growth are likely to go up with stronger effects on local employment rates, and less effect on population growth, as this provides greater benefits for local residents with strong local ties and has more positive fiscal effects. As for the zero-sum game argument, it seems likely that if local growth, for whatever reason, has differential effects on local employment to population ratios in different types of local areas, then redistributing growth toward areas with large effects on local employment to population ratios is likely to raise overall employment. The basic idea is simple. Growth shocks that redistribute local employment among local areas also redistribute population. The population changes in the different local areas must sum to zero. If local employment rates show sufficiently greater responsiveness in some local areas, then population and employment redistribution to such local areas will tend to raise aggregate employment. The intuition is that if an area has a large responsiveness of employment to population ratios to relative growth shocks, holding national economic trends constant, then that area has more untapped labor supply, and redistributing national growth toward that area raises the effective national labor supply.

MODEL AND DATA

This paper reports estimates of how the effects of metropolitan area growth on a metropolitan statistical area's (MSA) employment rate vary with the initial "tightness" of the metropolitan area's labor market. The model estimated is a pooled cross-section time-series model, with the observations derived from data on MSA/year cell means for 38 MSAs, from

1979 to 2004. Data on employment rates come from household data from the Outgoing Rotation Group of the Current Population Survey (CPS-ORG), whereas data on MSA employment growth is derived from establishment-based data from the U.S. Bureau of Economic Analysis (BEA).

The equations estimated take the following form:

$$(3) \qquad \ln(E/P)_{mt} - \ln(E/P)_{mt-1} = B(L)G_{mt} + C(L)G_{mt} * U_{mt(\mathrm{l})} + U_{mt(\mathrm{l})} + \text{Year dummies} + e_{mt}.$$

The equation symbols stand for the following variables:

- e_{mt} is the random disturbance term for MSA *m* in year *t*.
- E / P_{mt} is the mean ratio of employment to population for 16–64-year-olds in MSA *m* in year *t*, measured using data from the CPS-ORG. As will be explained below, this mean ratio is statistically adjusted for the demographic composition of the CPS sample of that particular MSA/year cell.
- G_{mt} is the employment growth from year $t-1$ to year *t* in MSA *m*, measured as the change from year $t-1$ in year *t* in the natural logarithm of employment. Employment is total employment in the MSA year cell as measured using establishment based data, primarily from the BEA.
- $B(L)$ indicates that current and lagged values will be included in growth, that is the logarithmic growth from year $t-1$ to year *t* is included as the current growth variable or zeroth lag, and we experiment with up to 10 lags in employment growth in different specifications.
- $U_{mt(\mathrm{l})}$ is a lagged measure of the level of mean labor market conditions in MSA *m* at lag l before year *t*. I experiment with a number of different measures of labor market conditions, including the employment to population ratio, the unemployment rate, and various logarithmic transformations of these variables. Labor market conditions are measured using data from the CPS-ORG. I experiment with both unadjusted MSA/year means for labor market conditions, and MSA/year means adjusted for demographic conditions. The lag length equals one lag more than the number of lags of growth included in a particular specification, that is, if the maximum lag in growth is the *k*th lag,

of $G_{mt-k} = \ln E_{mt-k} - \ln E_{mt-k-1}$, the lagged level of labor market condition variable included is U_{mt-k-1}. This means that the labor market condition is defined as of the year on which the maximum lag of growth is based, and all the growth variables are hence interacted with "initial labor market conditions" at the start of the initiation of the sequence of growth terms included. To ensure that the interaction terms reflect the interaction between growth and initial labor market conditions, and not the direct effect of initial labor market conditions, I also include lagged labor market conditions by itself as a control variable.

In this specification, the dynamic effects of growth shocks, up to the maximum growth lag considered, are completely described by simply considering the coefficients on the growth variables and their interaction with initial labor market conditions. For example, the effects of growth on the employment rate after *k* years are the sum of all growth coefficients up to *k* years, plus the sum of the growth interaction with the initial labor market condition variable up to the *k*th lag multiplied by the initial labor market condition variable. It is these growth effects up to the *k*th lag, which are estimated with complete flexibility by this functional form, that are the focus of attention in the paper. Because labor market conditions are endogenous, the long-run dynamics of the system, beyond the maximum lags of growth included, are in general affected by the coefficient on lagged labor market conditions and the interaction terms with growth. (The exception to this generalization would be if the lagged labor market condition variable by itself is zero and future growth is always zero.) However, I do not focus on these long-run dynamics, which in any event are significantly constrained by the functional form.

Year dummies are included. This means that implicitly all estimates are for the effects of differential employment growth shocks, that is, for shocks holding national time period effects constant and redistributing employment growth to this particular MSA. Including year dummies is, of course, equivalent to differencing all variables, including the change in employment to population ratios in the MSA, and MSA growth, from the national average for these same variables for that year.

In analyzing the CPS-ORG data to calculate MSA/year means, I exclude all observations for which the Census Bureau "allocated" the employment status data; that is, substituted for a missing value for an individual the employment status for a similar individual, who the Census Bureau does not require to be in the same metropolitan area. I use data for 38 metropolitan areas for which it is possible to define MSAs in the CPS-ORG that do not change dramatically from one year to the next at any time from 1979 to 2004. Table 1 lists the MSAs included. An appendix describes the change in county definitions in the CPS-ORG MSAs that are used in this paper.

The total employment data used is establishment data from the BEA. To define MSA employment growth, for all years I use the metropolitan area definitions from 2004. For some of the instrumental variable regressions, discussed below, I use detailed industry data to form predicted employment growth based on the MSA's industry mix and national growth by industry. The suppressions in the BEA and its lesser industry detail are overcome by using BLS data, and using interpolation and extrapolation to estimate suppressed industry employment numbers. The procedures for doing this are described in an appendix.

The mean MSA employment to population ratio variable is always, and the mean level of MSA labor market condition variables is sometimes, adjusted for various characteristics of the population based on a number of initial probit estimations of how individual characteristics affect these zero-one labor market status variables for an individual. For each year, I estimate a separate probit equation for each type of labor market status variable (the employment to population ratio, the unemployment rate) as a function of a quartic in age, discrete variables for education (high school dropout, high school graduate but no more, some college, and college graduates or more), discrete variables for race (white, black, Hispanic, other, but defined mutually exclusively with Hispanic status overriding the racial classification), a discrete variable for marital status, a discrete variable for gender plus an interaction between the gender variable and all other demographic characteristic variables, and finally, a set of discrete variables for the 38 MSAs. These probit equations are separately estimated for each year using individual data for all 16–64-year-olds in each year, with CPS person weights used in the estimation.

To do the "adjustment," we want to somehow measure how employment rates or unemployment rates vary across MSA/year cells holding constant the characteristics of individuals; that is, we want to measure the pure effect of being in a particular MSA and year and suppress variation in MSA/year means due to differences across MSA/year cells in the average characteristics of individuals. To do this, we take the 2004 national sample of 16–64-year-olds, and calculate the mean employment rate or unemployment rate for that sample if they were placed in a particular year and MSA by using the probit coefficients for that MSA and year, but assuming the entire 2004 U.S. sample was in the particular MSA being considered. In doing this calculation of adjusted means, I also use the CPS person weights.

As mentioned, I experiment with different functional forms and adjustments for the initial labor market condition variable. I start with the same functional form and adjustment used for the dependent variable; that is, I include as the lagged labor market condition variable the ln(mean employment to population ratio for MSA m and year *t*, adjusted using the probit procedure outlined above). I also try adjusted mean employment to population ratio; ln(1−adjusted mean employment to pop ratio); adjusted unemployment rate; ln(adjusted unemployment rate); and ln (1−adjusted unemployment rate = employment to labor force ratio). I also include unadjusted mean versions of all these variables.

I explore different functional forms because we have no real idea from theory or previous research for how labor market "tightness" should be measured. It is unclear whether the availability of labor is best measured by employment to population ratios or employment to labor force ratios. It is also unclear whether the availability of labor varies linearly with these variables or varies with percentage changes in these variables. Furthermore, it is unclear exactly how the availability of different types of labor affects the total effective quantity of available labor. Unadjusted versions of these variables assume that the raw number of nonemployed persons or unemployed persons is what matters, whereas the adjustment procedure assumes that the availability of individuals who, in national data, are more likely to be employed, matters more.

The initial interaction examined is a linear interaction between the growth variables and each of these functional forms for lagged labor market conditions. However, I also examine adding quadratic terms, or simply using discrete values for different levels of initial labor market conditions.

I also experiment with different lag lengths. Because of the pooled time-series cross-section nature of the data, each additional lag in growth that is included requires sacrificing 38 observations, one for each MSA. To test which lag length is optimal, I try all possible lag lengths from zero lags to 10 lags (11 different specifications), and in each case calculate an F-test for the last lag. The hope is that it will be clear which specification represents the best trade-off between explanatory power and loss of degrees of freedom.

Because the initial labor market condition variables are based on the CPS-ORG, the sample size for some MSA/year cells is modest, which raises issues of measurement error. Table 2 presents some descriptive statistics on the number of observations in each MSA/year cell. The issue of measurement error in local area cell means using CPS data has previously been raised in critiques by Bartik (1993) and Rowthorn and Glyn (2006) of Blanchard and Katz's article (1992) on state labor markets. The measurement error in CPS-ORG measures of the dependent variable does not cause any bias in the estimated coefficients in Equation (3) (although it adds to the imprecision of the estimation), but measurement error in the lagged initial labor market condition variables will bias the interaction term coefficients toward zero. To correct for this bias, most of the estimated equations base the lagged initial labor market condition variables included on the right-hand side only on the "even months" from the CPS-ORG, and instrument for these variables with the "odd months" from the CPS-ORG. This instrumental variable procedure was inspired by research by Blanchflower and Oswald (2005), who in turn were inspired by work by Staiger, Stock, and Watson (2002). The rationale for this procedure is that, given the design of the CPS, none of the households in the ORG that are interviewed in the even months (February, April, etc.) are the same as the households interviewed in the odd months (January, March, etc.).Therefore, these two variables are independent estimates of the same MSA/year means. The odd month variable will be a good instrument for the even month variable because the odd month variable is correlated with the true variation in the even month variable, but uncorrelated with the measurement error in the even month variable. This instrumental variable procedure should correct for any downward bias in estimated coefficients due to measurement error.

Previous studies have suggested that over periods of a few years, variations in employment growth across different local economies are mostly labor-demand-driven (Bartik 1991; Blanchard and Katz 1992). It is the effects of demand-driven employment growth on local employment rates that we are trying to measure. However, in theory, some of the short-run variation across local economies in employment growth could be labor-supply-driven. One would expect employment growth shocks that are labor-demand-driven to have quite different effects on local employment to population ratios from shocks to employment growth that are driven by labor supply shocks. Shocks to labor demand will tend to increase employment to population ratios, which will put upward pressure on wages, with both higher employment to population ratios and higher wages tending to attract population in-migration. Shocks to labor supply from migration will tend to decrease employment to population ratios and wages, and these decreases will tend to attract additional employment to an MSA. To make sure that the particular data used here is consistent with previous research that short-run local employment growth shocks are predominantly labor demand driven, I experiment with instrumenting for actual employment growth. The instrument used is the employment growth predicted by the share component of a shift-share analysis, which is the employment growth predicted if each industry in the metropolitan area just grew at the industry's national growth rate. This type of instrument has previously been used to proxy for demand-driven employment growth by Bartik (1991), Blanchard and Katz (1992), and Blanchflower and Oswald (1994). As shown in Bartik (1991), this share effect instrument is a proxy for changes in local employment due to national demand for the local area's export-base industries.

Table 3 reports the means and standard deviations for some of the key variables.

RESULTS

I first consider a version of Equation (3) that includes as an interaction variable lagged labor market conditions defined as ln(adjusted employment to population ratio). For this version, I test all possible lag lengths from zero to 10 lags, which include 11 possible lag lengths.

Table 4 reports the F-tests for the last lag in each of these 11 specifications. Based on these F-tests, the two-lag specification clearly seems preferable. The 2nd lag is clearly significant in the two-lag specification, whereas the last lag is never statistically significant at less than a 5 percent level in any specifications with more lags. Only the 8th lag is even close to statistical significance at the 5 percent level. Furthermore, going from 2 to 8 lags requires sacrificing many degrees of freedom, and would almost surely not be optimal by most reasonable model selection procedures.

This relatively short lag length is consistent with other studies that suggest that the effects of growth on local labor market variables have effects that vary some over time, but typically settle down to a new equilibrium within a few years (Bartik 1991).

I then consider possible functional forms for which type of initial labor market conditions may matter most in determining the potential effects of growth on local employment rates. This exploration of functional form always uses a two-lag specification. The initial labor market condition variables considered as interaction terms with the growth variables include employment to population ratios and employment to labor force ratios, and various manipulations of these variables, and both adjusted and unadjusted versions of both types of variables. (That is, adjusted for local labor market mix or not). The resulting F-tests for the interaction terms are reported in Table 5.

The results in Table 5 suggest that adjusted initial labor market condition variables matter more to the effects of growth on local employment rates than do unadjusted labor market condition variables. In addition, employment to population ratios matter more to the effects of growth than do employment to labor force ratios. Finally, among the employment to population ratio alternatives, the natural log of (1 − the adjusted employment to population ratio), the natural log of the adjusted nonemployment rate, tends to result in the best statistical fit.

A possible interpretation of the Table 5 results is that adjusting for local demographic conditions gives a better statistical fit because available labor matters more if this labor would be usually expected to be employed in the national sample, which implies that this available labor is more employable. In addition, apparently the available labor supply that can be tapped through growth is better captured by looking at everyone who is not employed rather than just those who are officially unemployed. Finally, in terms of functional form, apparently a given change in the employment rate matters more when the employment rate is very high (or nonemployment rate is very low).

Table 6 reports results, in its first column of results, for the optimal lag length and functional form specification. I then consider possible modifications to the estimation approach for this specification. I do a Hausman test of whether or not the 2SLS estimation to correct for measurement error in initial labor market conditions actually results in statistically significantly different results. The Hausman test suggests that the measurement error correction using the odd months as instruments does not in fact result in statistically significantly different estimates. (The

Chi-squared statistic is 7.97 with 29 degrees of freedom, and the probability of having a C Chi-squared of that size or greater when the two sets of estimates are converging to the same parameters is almost 1. Furthermore, it should be pointed out that the F-tests on the odd month instruments in the first stage estimation suggest that the instruments used are quite good predictors for the analogous even month variables, as the F-tests on the four excluded instruments—which are the odd month estimation of the adjusted means by itself and interacted with the three growth variables—for the four endogenous variables are 271.68; 289.65; 332.67; and 332.85; where the lagged labor market variable by itself is reported first, and then the interaction terms from the zeroth to the 2nd lag.)

This finding suggests that we do not need to do this measurement error correction, and that it would be preferable to do OLS, with all the odd and even month data used to measure initial labor market conditions. When we do this, we get the results reported in the second column of results in Table 6.

We might also wonder about whether or not local growth shocks are mainly due to labor demand shocks. As mentioned above, we would expect local employment growth due to labor supply shocks to have different effects on employment to population ratios than shocks to local employment growth due to labor demand shocks.

After instrumenting for the employment growth variables with predicted growth due to local industrial mix and national growth of different industries, a proxy for export-base shocks to local employment growth, we get the results in the third column of results in Table 6. Although the estimated effects are a little greater, Hausman tests suggest that the results are not statistically significantly different. (The Hausman Chi-squared statistic, with 29 degrees of freedom, is 5.04, and the probability of a Chi-squared equal to or greater than this value when the two sets of estimates are converging to the same parameter values is essentially unity. Furthermore, F-tests on the six excluded share effect instruments for the six endogenous variables—the growth terms and the interaction terms with growth—are 35.16; 31.38; 41.36; 196.48; 185.67; and 334.02; where these F-tests are ordered with growth terms from zeroth to second lag first, and then the interaction terms in the same order. Therefore these share effect instruments are quite good predictors of actual employment growth.)

Focusing on the OLS results in Table 6, the results at the means of the nonemployment rate match closely with previous research (see reviews in Bartik 1991, 1993, 2001). Local employment growth shocks appear to initially have about 40 percent of their effect reflected in higher employment to population ratios, with the remaining 60 percent being reflected in higher local population. Local growth's average effects on local employment to population ratios quickly decline to about 20 percent of the total effect of local growth, with the remaining 80 percent being reflected in higher population.

The interaction terms between local growth and initial labor market conditions are jointly statistically significant. However, the cumulative interaction effects are only statistically significant after one year. The point estimates all indicate that growth's effects on local employment rates are higher when the initial nonemployment rate is higher. A 10 percent increase in the local area's initial nonemployment rate (in log percentage terms) increases growth's effects on local employment rates by 0.11 after one year, but by only 0.02 after two years. A 10 percent increase in the nonemployment rate at the mean value of the nonemployment rate of 0.271 is about 2.7 percentage points in the nonemployment rate stated in percentage-point terms. A one standard deviation increase in initial local nonemployment rates is a little more than 10 percent of the mean nonemployment rate of 0.271. (As seen in Table 3, the standard deviation of the employment rate or the nonemployment rate is 0.035; the directly measured standard deviation of the local ln(nonemployment rate) is 0.13.)

I also explored other functional forms for how the initial nonemployment rate alters the effect of growth on employment rates. The addition of quadratic terms in the natural log of the initial nonemployment rate is marginally statistically significant, at about the 19 percent level. The quadratic results are reported in Table 7.

In addition, I looked at how growth effects on employment rates varied at different levels of the initial employment rate by dividing the initial employment rate into quintiles, and interacting dummy variables for the quintiles with the growth terms. The F-test for the statistical significance of these quintile interaction terms is also marginally statistically significant, at a little less than 20 percent. These quintile results are reported in Table 8.

Figures 1, 2, and 3 graphically present the original, simple interaction results, the quadratic results, and the quintile results for how the effects of growth vary at different lags. (Table 9 gives the numbers underlying these figures.) At zero and one lag, all three functional forms for the interaction give similar results. These results suggest that local areas with initially lower nonemployment rates have lower effects of growth on local employment rates, particularly after one year.

The cumulative effects at two lags suggest that the linear interaction results may not fully capture the complexity of how growth's effects at two years vary with the initial employment rate. The quadratic and quintile interaction results suggest that growth effects on local employment rates may be lower in local areas with the initially lowest nonemployment rates. On the other hand, at some point, local areas with higher nonemployment rates do not show stronger effects of growth on local employment rates, and may even show some weaker effects on local employment rates in local areas with the initially highest nonemployment rates.

In Table 8, statistical tests for the differential quintile effects provides suggestive evidence that after two lags, the cumulative effects of employment growth in the very lowest nonemployment rate areas are relatively low. The highest effects of employment growth on employment rates after two years are in the areas that initially have nonemployment rates that are somewhat above average, but not too far above.

Presumably, the low effects of growth on local employment rates in areas with the lowest nonemployment rates reflect the lack of available labor, which leads to almost all the effects of growth after two years being reflected in increased in-migration. Why might growth effects on local employment rates also be smaller in local areas that initially have the highest nonemployment rates? One could speculate that in these metropolitan areas, lack of growth might have resulted in considerable out-migration, and that therefore extra growth leads to a population increase due to averted out-migration. It is the metropolitan areas that initially have the middle range of local nonemployment rates in which growth shocks have the most persistent effects on local employment rates, and the lowest effects on net population growth.

Another possibility to consider is that although the 2SLS estimates with share-effect instruments do not show statistically significant overall differences from the OLS estimates, perhaps there are some differences in individual coefficients that are important. For example, one could speculate that in the local areas with the initially highest nonemployment rates, subsequent employment growth rates tend to be slower due to population out-migration, a supply shock, which will tend to bias the estimates of effects of employment growth in these types of local labor markets.

To test this hypothesis, I reestimated the quintile specification using 2SLS, with share effects of employment growth used to create instruments. Table 10 reports these 2SLS estimates, and also reports the OLS estimates for comparison. These 2SLS estimates do provide some modest evidence that the OLS estimates may understate the true effects of demand shocks in the long run in the local areas with the highest nonemployment rates. The 2SLS pattern of effects after two years is simpler to describe, with employment growth causing significant effects on employment rates, in the three highest quintiles of initial nonemployment rates, of about 30 percent of the employment growth shock, with the remaining 70 percent of the employment growth being accommodated by increased population; in contrast, in the two lowest quintiles of initial nonemployment rates, employment growth after two years only leads to population growth increases, with no effect on local employment rates. However, although the 2SLS pattern of point estimates is sensible, the 2SLS estimates are imprecise enough that differences of these estimates from the OLS estimates, or differences of 2SLS quintile effects from the average effects across quintiles, are usually only of modest statistical significance.

CONCLUSION

Employment growth has different effects on local employment to population ratios in different metropolitan area labor markets, with the differences being clearest in short-run responses. Over the longer run, the largest effects of growth on local employment rates are in metropolitan areas that are average or slightly below average in initial labor market tightness. In the areas with the lowest initial nonemployment rates, local growth appears to have little effect on employment rates after just two years.

These findings imply that local employment growth will pay off the most in local benefits in metropolitan areas that have some labor market problems, but are not so troubled that they are about to lose significant population. Redistributing growth to these areas with labor market problems, and away from areas with low nonemployment rates, is most likely to expand the effective national labor supply and hence expand national employment. Finally, these results also imply that labor market tightness is better measured by looking at the nonemployment of the entire population of working age, and by putting greater weight on the availability of persons who seem based on national data to be more employable.

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Table 1. Metropolitan Areas Included in This Study

MSA	Area name
1	Akron
2	Albany-Schenectady-Troy
3	Atlanta
4	Baltimore
5	Birmingham
6	Boston
7	Buffalo-Niagara Falls
8	Chicago
9	Cincinnati
10	Cleveland
11	Columbus
12	Dallas-Fort Worth
13	Denver
14	Detroit
15	Greensboro
16	Houston
17	Indianapolis
18	Kansas City
19	Los Angeles
20	Miami
21	Milwaukee
22	Minneapolis
23	New Orleans
24	New York
25	Philadelphia
26	Pittsburgh
27	Portland
28	Riverside-San Bernardino
29	Rochester
30	Sacramento
31	St. Louis
32	San Diego
33	San Francisco-Oakland
34	San Jose
35	Seattle
36	Tampa
37	Virginia Beach-Norfolk
38	Washington DC

Table 2. Distribution of Observations per MSA/Year Cell in These CPS-ORG Data, 38 Metropolitan Areas and 26 Years (1979–2004)

	Mean MSA/year cell size	Standard deviation of MSA/year cell size	Minimum cell size	Maximum cell size	Median cell size	5th percentile of cell size	95th percentile of cell size
Number of persons	2,474	2,660	421	17,306	1,548	695	8,105

NOTE: All statistics are based on underlying number of persons in each of the 988 MSA/year cells (38 MSAs × 26 years).

Table 3. Means and Standard Deviations for Some Key Variables

Variable	Mean	Standard deviation
MSA employment growth (= change in natural log of employment from last year to this year)	0.0176	0.0210
Adjusted employment to population ratio	0.7297	0.0350
Unadjusted employment to population ratio	0.7206	0.0476
Adjusted employment to labor force ratio	0.9345	0.0221
Unadjusted employment to labor force ratio	0.9389	0.0223

NOTE: Statistics are based on observations on the means or adjusted means for 988 MSA/year cells. The ratio variables are based on levels of variables for 38 MSAs from 1979 to 2004, whereas the growth variable is based on year to year change in employment for 38 variables for the years 1978–1979 through 2003–2004. As mentioned in the text, the adjusted figures are based on a prediction of what would be the mean value of these ratios if the entire 2004 national sample was somehow “moved” to a particular MSA/year cell. As the 2004 sample tends to be somewhat more educated, the mean adjusted employment to population ratio tends to be greater than the unadjusted ratio. However, in adjusting the employment to labor force ratio, because the adjustment uses the entire 2004 national sample, not just those in the labor force, the mean adjusted employment to labor force ratio is slightly below the unadjusted ratio, as the entire 16–64 population is somewhat more “disadvantaged” than those in the labor force.

Table 4. F-tests on Last Lag of Growth Included in Specifications with 11 Different Lag Lengths

Number of lags of growth included	F-test on all last lag of growth terms	Probability of F-test equal to or exceeding that level if last lag coefficients were truly zero	Number of observations included in estimation
0	34.972	lt 0.0001	950
1	2.524	0.0807	912
2	6.926	0.0010	874
3	1.861	0.1561	836
4	0.910	0.4029	798
5	1.544	0.2141	760
6	0.696	0.4990	722
7	0.710	0.4919	684
8	2.339	0.0973	646
9	0.082	0.9210	608
10	1.814	0.1639	570

NOTE: This table summarizes some results from estimations of 11 different specifications for explaining the year to year change in the natural log of the adjusted employment to population ratios. Each model follows the template set out as Equation (3) in text. Each equation includes a complete set of year dummies. All specifications include current employment growth and an interaction of current growth with some lag of the natural log of the adjusted employment to population ratio. All specifications also include the lag of the natural log of the adjusted employment to population ratio by itself. The specifications vary in including from zero to 10 lags in growth, and zero to 10 lags in the interaction term with the lagged natural log of the adjusted employment to population ratio. The F-tests reported are for including the last lag in growth plus the last lag of growth interacted with the lag of the natural log of the adjusted employment to population ratio. Adding one additional lag in growth requires sacrificing one year of data for each of the 38 MSAs.

Table 5. F-tests Comparing the Statistical Significance of Interaction Terms Between Growth Terms and Various Functional Forms for Lagged Initial Labor Market Condition Variables

Functional form of lagged initial labor market condition interaction term	F-test on all interaction terms	Probability of F-test of that size or greater if true coefficients on interaction terms were zero
log(adj.emppop)	3.933	0.0084
adj.emppop	3.994	0.0077
log(1−adj.emppop)	4.155	0.0062
emplf	1.967	0.1173
log(adj.emplf)	1.940	0.1215
log(1−adj.emplf)	2.314	0.0746
unadj.emppop	1.512	0.2100
log(unadj.emppop)	1.512	0.2101
log(1−unadj.emppop)	1.535	0.2040
unadj.emplf	0.615	0.6054
log(unadj.emppop)	0.604	0.6126
log(1−unadj.emppop)	0.783	0.5034

NOTE: All estimates are for 2-lag specification, with 874 observations. Hence, number of interaction terms involved in F-tests are always three terms. Furthermore, the lagged labor market condition variable is always the third lag of the labor market condition variable. The acronyms used are that emppop is the employment to population ratio, and emplf is the employment to labor force ratio. “Adj.” and “unadj.” refer to whether the estimated cell means for the lagged labor market condition variable are “adjusted” for the demographic composition of each MSA/year cell using the procedure outlined in the text.

Table 6. Estimated Cumulative Effects of Local Employment Growth on Employment Rates, With Effects Varying With Initial Log of Nonemployment Rate, Three Different Estimation Methods

Cumulative effect of growth	After	Instrumenting for lagged labor market condition variables	OLS estimates	Instrumenting for growth variables
At mean lagged nonemployment rate	0 lags	0.377 (5.60)	0.378 (5.69)	0.463 (2.96)
At mean lagged nonemployment rate	1 lag	0.342 (4.81)	0.336 (4.77)	0.528 (3.16)
At mean lagged nonemployment rate	2 lags	0.193 (3.38)	0.183 (3.27)	0.211 (1.71)
Interacted with lagged ln(nonemployment rate)	0 lags	0.365 (0.80)	0.394 (1.05)	0.536 (0.99)
Interacted with lagged ln(nonemployment rate)	1 lag	1.529 (3.34)	1.146 (2.95)	1.416 (2.69)
Interacted with lagged ln(nonemployment rate)	2 lags	0.257 (0.62)	0.245 (0.70)	0.738 (1.29)
Probability of the F-test on the interaction terms		0.0062	0.0201	0.0574

NOTE: All these estimates are for a two-lag specification. Numbers in cells are estimated effects, with t-statistics for estimated effects in parentheses. Equations are reformulated so that what is reported is cumulative effects of growth after zero lags (zeroth growth term), one lag (sum of two growth terms), and after two lags (sum of three growth terms). Furthermore, equations are reformulated so that cumulative effects of growth are stated at mean value of nonemployment rate of 0.271 (This is mean value of lagged nonemployment rate, so it differs slightly from mean value of overall nonemployment rate). The interaction terms are then interpreted as effects of cumulative effects of growth interacted with deviations from that mean value. All specifications include a complete set of year dummies, and the lagged labor market condition variable by itself. The number of observations is 874 for each of the three specifications. The lagged labor market condition variable by itself has coefficients (t-stats) in the three specifications, in the order the three columns are presented, of 0.009 (0.77); 0.009 (1.02); and, −0.002 (−0.15).

Table 7. Allowing for Quadratic Terms in How Effects of Local Growth on Employment Rates Varies With Initial Labor Market Conditions

Cumulative effects of employment growth	After	Specification that only allows interaction with ln(nonemplrate)	Specifation that adds quadratic interation terms
At mean initial nonemployment rate	0 lags	0.378 (5.69)	0.396 (5.37)
At mean initial nonemployment rate	1 lag	0.336 (4.77)	0.340 (4.30)
At mean initial nonemployment rate	2 lags	0.183 (3.27)	0.243 (3.64)
Interacted with differential of lagged ln(nonemployment rate) from mean	0 lags	0.394 (1.05)	0.477 (1.23)
Interacted with differential of lagged ln(nonemployment rate) from mean	1 lag	1.146 (2.95)	1.254 (3.12)
Interacted with differential of lagged ln(nonemployment rate) from mean	2 lags	0.245 (0.70)	0.335 (0.94)
Interacted with squared differential of lagged ln(nonemployment rate) from mean	0 lags		−0.764 (−0.37)
Interacted with squared differential of lagged ln(nonemployment rate) from mean	1 lag		0.359 (0.17)
Interacted with squared differential of lagged ln(nonemployment rate) from mean	2 lags		−3.590 (−1.75)

NOTE: Both equations are estimated by OLS, and include all interaction terms separately in regression. F-test on addition of three quadratic terms has value of 1.59, and probability of 0.1910. Number of observations in both specifications is 874. T-statistics are in parentheses.

Table 8. Allowing for Effects of Local Growth on Employment Rates To Vary Flexibly with Different "Quintiles" of Initial Labor Market Conditions

Cumulative effects of employment growth	After	Specification that only allows interaction w/ ln(nonemplrate)	Specification that substitutes interaction with lagged quintiles of nonemployment distribution	Nonemployment quintile: Highest	2nd highest	3rd highest	4th highest	5th highest (lowest)
At mean initial nonemployment rate	0 lags	0.378 (5.69)	0.396 (5.89)					
At mean initial nonemployment rate	1 lag	0.336 (4.77)	0.332 (4.66)					
At mean initial nonemployment rate	2 lags	0.183 (3.27)	0.177 (3.10)					
Interacted with differential of lagged ln(nonemployment rate) from mean	0 lags	0.394 (1.05)						
Interacted with differential of lagged ln(nonemployment rate) from mean	1 lag	1.146 (2.95)						
Interacted with differential of lagged ln(nonemployment rate) from mean	2 lags	0.245 (0.70)						
Differential from mean of different quintiles of lagged nonemployment distribution	0 lags			0.009 (0.10)	0.110 (1.15)	0.011 (0.12)	−0.024 (−0.26)	−0.106 (−1.07)
Differential from mean of different quintiles of lagged nonemployment distribution	1 lag			0.222 (2.25)	0.057 (0.56)	0.019 (0.20)	−0.064 (−0.62)	−0.235 (−2.36)
Differential from mean of different quintiles of lagged nonemployment distribution	2 lags			-0.058 (-0.70)	0.123 (1.44)	0.098 (1.03)	−0.026 (−0.27)	−0.136 (−1.45)

NOTE: Both specifications use 874 observations. Numbers in cells are estimated cumulative effects or, in parentheses, estimated t-statistics on these estimated effects. Both specifications provide estimates of "average" cumulative effects of growth on employment rates, either at the mean lagged nonemployment rate, or the average over all five quintiles. The quintile interaction terms are for deviations of the cumulative quintile effect from the average cumulative effect over all five quintiles. The quintiles are defined as follows: nonemployment greater than 0.302; between 0.302 and 0.278; between 0.278 and 0.259; between 0.259 and 0.237; nonemployment less than 0.237. The mean nonemployment rate for each of the five quintiles is 0.322; 0.289; 0.268; 0.249; 0.222. The F-test probabilities are: all quintile interaction terms, 0.01958; interactions at zero lags: 0.7458; interactions at one lag: 0.0742; interactions at two lags: 0.3191.

Table 9. Estimated Effects of Local Employment Growth on Employment Rates at Means of Lagged Quintiles of Nonemployment Rate, Three Different Specifications for Interaction Terms

Quintile	Mean nonemployment rate in each initial nonemployment rate quintile	0 Lags; Specification:			1 Lag; Specification:			2 Lags; Specification:		
		quintile	simple interaction	quadratic	quintile	simple interaction	quadratic	quintile	simple interaction	quadratic
Q1	0.322	0.405	0.446	0.456	0.555	0.534	0.567	0.119	0.185	0.194
Q2	0.289	0.506	0.403	0.424	0.390	0.410	0.422	0.299	0.184	0.250
Q3	0.268	0.407	0.374	0.391	0.351	0.323	0.326	0.275	0.183	0.239
Q4	0.249	0.372	0.345	0.350	0.268	0.239	0.236	0.150	0.182	0.189
Q5	0.222	0.290	0.299	0.270	0.097	0.107	0.104	0.040	0.181	0.033

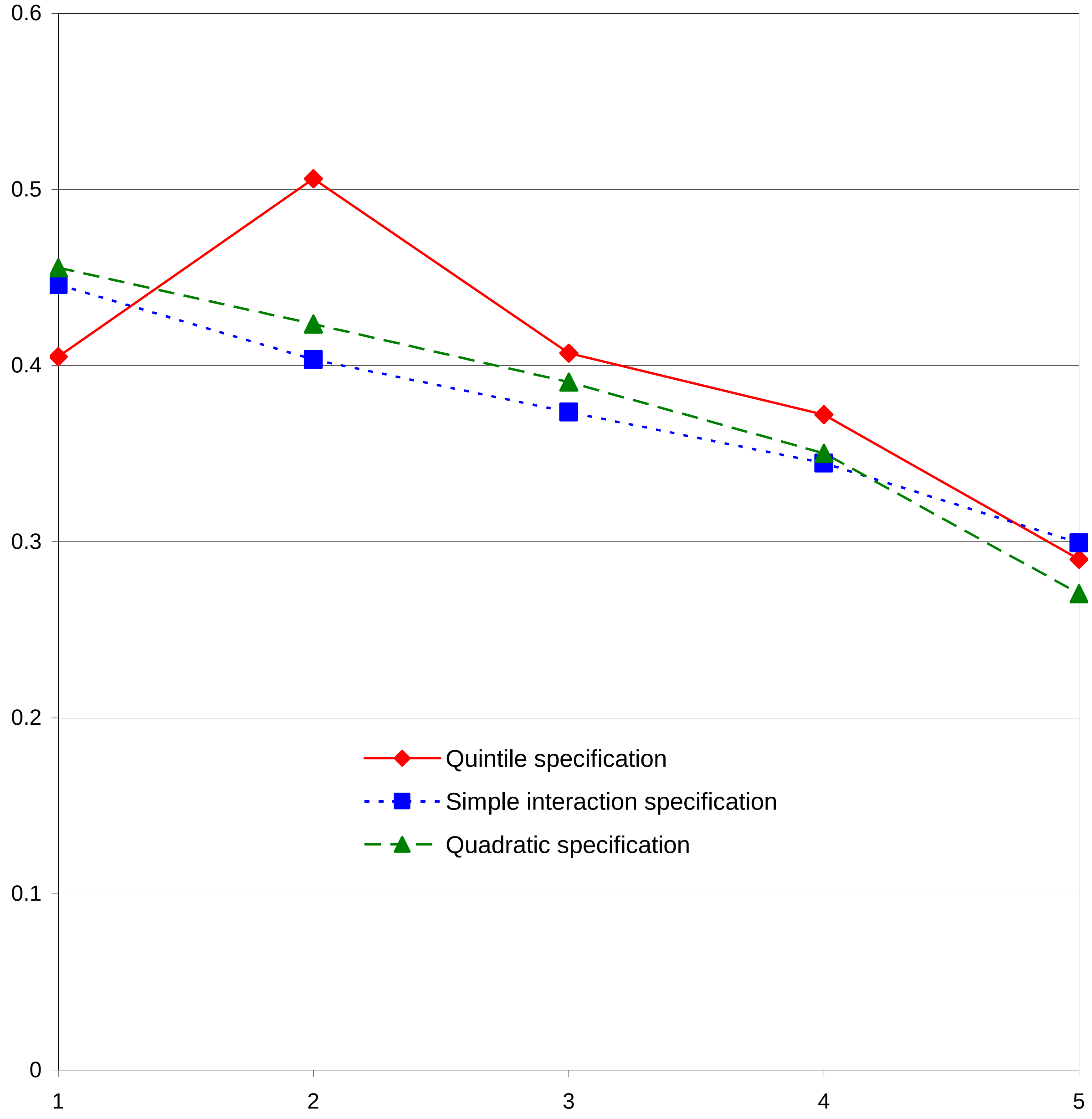
NOTE: These estimates use coefficient estimates from Tables 8 and 9 to estimate the effects of local employment growth on employment rates at the different means of the different quintiles of the lagged nonemployment rate. These are cumulative effects after different number of lags from three different specifications: a specification that interacts the growth terms with dummies for quintiles of the initial distribution; a specification that interacts the growth terms with the natural log of the nonemployment rate; a specification that allows squared interaction terms as well. These numbers are the basis for Figures 1, 2, and 3.

Table 10. Comparison of Variations in Growth Effects on Employment Rates at Different Initial Quintiles of Nonemployment Rates, OLS vs. 2SLS Estimates Using Demand Shock Instruments

	OLS Estimates	2SLS Estimates	Difference (2SLS minus OLS)
Avg. Effect, 0^{th} lag	0.396	0.429	0.033
	(5.89)	(2.74)	(0.23)
Avg. Effect, 1^{st} lag	0.332	0.470	0.138
	(4.66)	(2.82)	(0.92)
Avg. Effect, 2^{nd} lag	0.177	0.177	0.000
	(3.10)	(1.40)	(0.00)
0^{th} lag, Q1	0.405	0.497	0.092
	(3.51, 0.10)	(2.27, 0.49)	(0.49)
0^{th} lag, Q2	0.506	0.424	−0.082
	(4.17, 1.15)	(1.99, −0.04)	(−0.47)
0^{th} lag, Q3	0.407	0.416	0.009
	(3.72, 0.12)	(2.00, −0.10)	(0.05)
0^{th} lag, Q4	0.372	0.402	0.030
	(3.40, −0.26)	(2.13, −0.21)	(0.20)
0^{th} lag, Q5	0.290	0.406	0.116
	(2.36, −1.07)	(2.02, −0.17)	(0.72)
1^{st} lag, Q1	0.555	0.796	0.241
	(4.57, 2.25)	(3.64, 2.39)	(1.32)
1^{st} lag, Q2	0.390	0.555	0.165
	(2.99, 0.56)	(2.42, 0.62)	(0.91)
1^{st} lag, Q3	0.351	0.518	0.167
	(2.96, 0.20)	(2.38, 0.37)	(0.91)
1^{st} lag, Q4	0.268	0.305	0.037
	(2.15, −0.62)	(1.38, −1.12)	(0.20)
1^{st} lag, Q5	0.097	0.175	0.078
	(0.81, −2.36)	(0.94, −2.20)	(0.55)
2^{nd} lag, Q1	0.119	0.284	0.165
	(1.30, −0.70)	(1.71, 0.78)	(1.20)
2^{nd} lag, Q2	0.299	0.313	0.014
	(3.06, 1.44)	(1.80, 1.02)	(0.10)
2^{nd} lag, Q3	0.275	0.294	0.019
	(2.40, 1.03)	(1.37, 0.77)	(0.10)
2^{nd} lag, Q4	0.150	−0.012	−0.162
	(1.30, −0.27)	(−0.06, −1.29)	(−0.95)
2^{nd} lag, Q5	0.040	0.006	−0.034
	(0.35, −1.45)	(0.03, −1.33)	(−0.25)

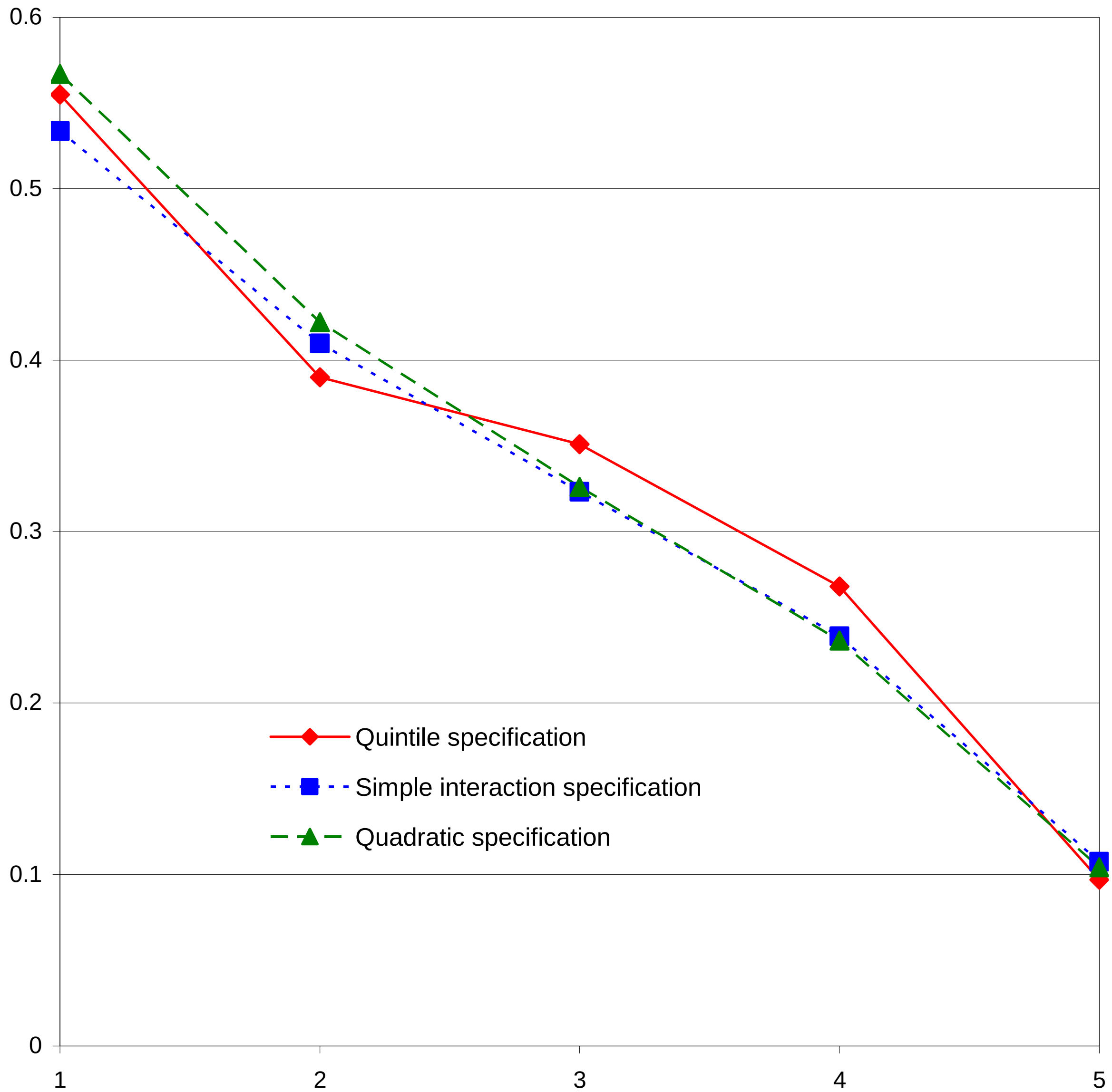
NOTE: Numbers in first two columns of results are cumulative effects, either at means or for different quintiles, for OLS and 2SLS estimation using share effect instruments. First number in parentheses is t-test for hypothesis that cumulative effect equals zero; second number in parentheses is t-test for hypothesis that quintile effect is no different from average effect across all quintiles. Last column reports differences between 2SLS and OLS cumulative effects, and t-statistic of that difference (variance of difference will equal variance of 2SLS effect minus variance of OLS effect).

Figure 1. How the Initial Effect of Local Employment Growth on Employment Rates Varies with Initial Values of the Nonemployment Rate, Three Different Specifications



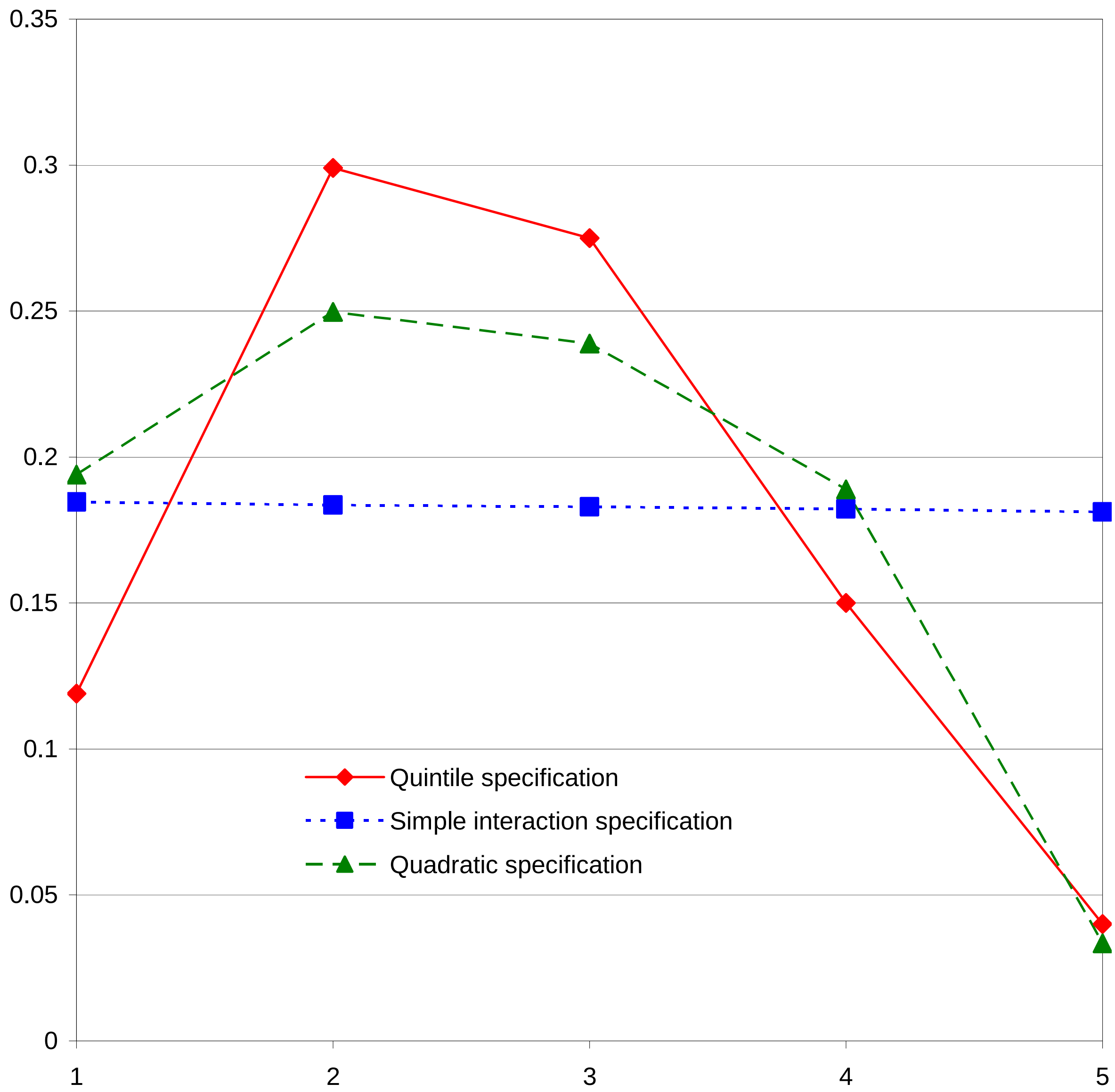
NOTE: These figures show the effects of local employment on employment rates at different lagged values of the nonemployment rate. The initial value of the nonemployment rate is divided up into quintiles of the initial nonemployment rate. In the figure, the highest nonemployment quintile is on the left and the lowest nonemployment rate is on the right. The numbers behind this figure are in Table 9, and in turn are based upon the estimates in Tables 7 and 8.

Figure 2. How the Effect of Local Employment Growth on Employment Rates After One Year Varies with Initial Values of the Nonemployment Rate, 3 Different Specifications



NOTE: These figures show the effects of local employment on employment rates at different lagged values of the nonemployment rate. The initial value of the nonemployment rate is divided up into quintiles of the initial nonemployment rate. In the figure, the highest nonemployment quintile is on the left and the lowest nonemployment rate is on the right. The numbers behind this figure are in Table 9, and in turn are based upon the estimates in Tables 7 and 8.

Figure 3. How the Effect of Local Employment Growth on Employment Rates After Two Years Varies with Initial Values of the Nonemployment Rate, Three Different Specifications



NOTES: These figures show the effects of local employment on employment rates at different lagged values of the nonemployment rate. The initial value of the nonemployment rate is divided up into quintiles of the initial nonemployment rate. In the figure, the highest nonemployment quintile is on the left and the lowest nonemployment rate is on the right. The numbers behind this figure are in Table 9, and in turn are based upon the estimates in Tables 7 and 8.